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Title: Inequality in Energy Consumption: Statistical Equilibrium or a Question of Accounting Conventions?

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Abstract
Mitigating climate change requires information about the inequality in energy consumption. Recent contributions (Banerjee and Yakovenko, 2010; Lawrence et al., 2013; Yakovenko, 2010, 2013) have studied energy inequality through the lens of maximum entropy. They claim a weighted international distribution of total primary energy demand should approach a Boltzmann-Gibbs maximum entropy equilibrium distribution in the form of an exponential distribution, implying convergence to a Gini coefficient of 0.5 from above. The present paper challenges the validity of this claim and critically discusses the applicability of statistical equilibrium reasoning to economics from the viewpoint of social accounting. It is shown that the exponential distribution is only a robust candidate for a statistical equilibrium of energy inequality when employing one particular accounting convention for energy flows, the substitution method. But this method has become problematic with a higher renewable share in the international energy mix, and no other accounting method supports the claim of a convergence to a 0.5 Gini. We conclude that the findings based on maximum entropy reasoning are sensitive to accounting conventions and critically discuss the epistemological implications of this sensitivity for the use of maximum entropy approaches in social sciences.

Keywords: global energy inequality, maximum entropy, social accounting

JEL codes: B40, D63, Q43

1. Introduction

Understanding inequality in per capita energy consumption at the global level delivers key insights for strategies to mitigate climate change.[1] Economic growth and per capita energy demand are tightly coupled (Csereklyei et al., 2016; Semieniuk, 2018), so energy inequality can be an important indicator of uneven economic development. Moreover, climate change mitigation now demands absolute reductions in the global average of energy per capita consumption (Rogelj et al., 2018; Semieniuk et al., 2019). Achieving this requires an understanding of the global energy consumption inequality. Current approaches such as carbon taxes can disproportionately hit the poor because of their higher share of energy consumption in expenditure (Boyce, 2018; Fremstad and Paul, 2019; Teixidó and Verde, 2017). Therefore, understanding the global distribution of energy consumption is key to grappling with the political economy of climate change mitigation (Jenkins, 2014). Finally,

[1] Strictly speaking and abiding by the First Law of Thermodynamics, energy cannot be consumed, just degraded. Sticking with common usage in social sciences we will nevertheless write consumption. We will also write energy inequality short for inequality in the per capita consumption of energy.

attempts at reducing global resource inequalities, which can render climate mitigation policies more feasible (Rao and Min, 2018), must know the extent of these inequalities.

Given the systemic importance of energy inequality, it is surprising to see the dearth of research on the extent and evolution of global energy inequality by economists, in contrast with much more extensive work in the area of income and consumption (Anand and Segal, 2015; Darvas, 2019; Galbraith and Berner, 2001; Lahoti et al., 2016; Milanovic, 2005; Milanović, 2016; Nino-Zarazua et al., 2016; Ravallion, 2019). The most recent analysis of global per capita energy inequality (proxied by taking country averages weighted by their population and therefore called weighted international inequality) appears to be over a decade old (Hedenus and Azar, 2005). Maza and Villaverde (2008) only consider electricity, and Duro (2015) does not weight observation by population. The theoretical blinder of 'convergence' in economic growth theory, focuses attention away from the extent of inequality at the macro level, as inequality appears as a transitory phenomenon (Duro et al., 2010); and at the micro level there are no global datasets. As far as climate change is concerned, one can also look 'directly' at greenhouse gas emissions (Chancel and Piketty, 2015). But there is a fundamental difference between energy (an input into production) and emissions, an unwanted output. Constraints on the former can inform insight into the latter, and ignorance about energy inequality forgoes an important piece of information for policy.

In light of this lacuna, the research by Victor Yakovenko and his co-authors stands out. In a series of papers, (Banerjee and Yakovenko, 2010; Lawrence et al., 2013; Yakovenko, 2010, 2013), they analyse the weighted international energy inequality from 1980 to 2010, computing Gini coefficients and Lorenz curves. Furthermore, analysing the results through the lens of maximum entropy, Yakovenko et al. predict that the distribution of total primary energy supply should approach a microcanonical Boltzmann-Gibbs equilibrium distribution. This distribution has the exponential form and implies a unique Gini coefficient of 0.5. The data they analyse strongly confirms their hypothesis. Thus, the work is both descriptive of historical data and predictive, by combining maximum entropy reasoning with inequality measures. However, in this paper we show that their hypothesis is not robust. We compute and compare Gini coefficients over time for different methods of accounting for primary, final and territorial versus footprint energy measures – the first such exercise to our knowledge. We show that Ginis vary by up to 0.1 units for the same year, and there is no sign of convergence to a particular value. Hence the validity of the 0.5 Gini finding based on maximum entropy reasoning is sensitive to accounting conventions. We explain the accounting conventions behind the divergent results and critically discuss the epistemological implications of this sensitivity for the use of maximum entropy approaches in social sciences.

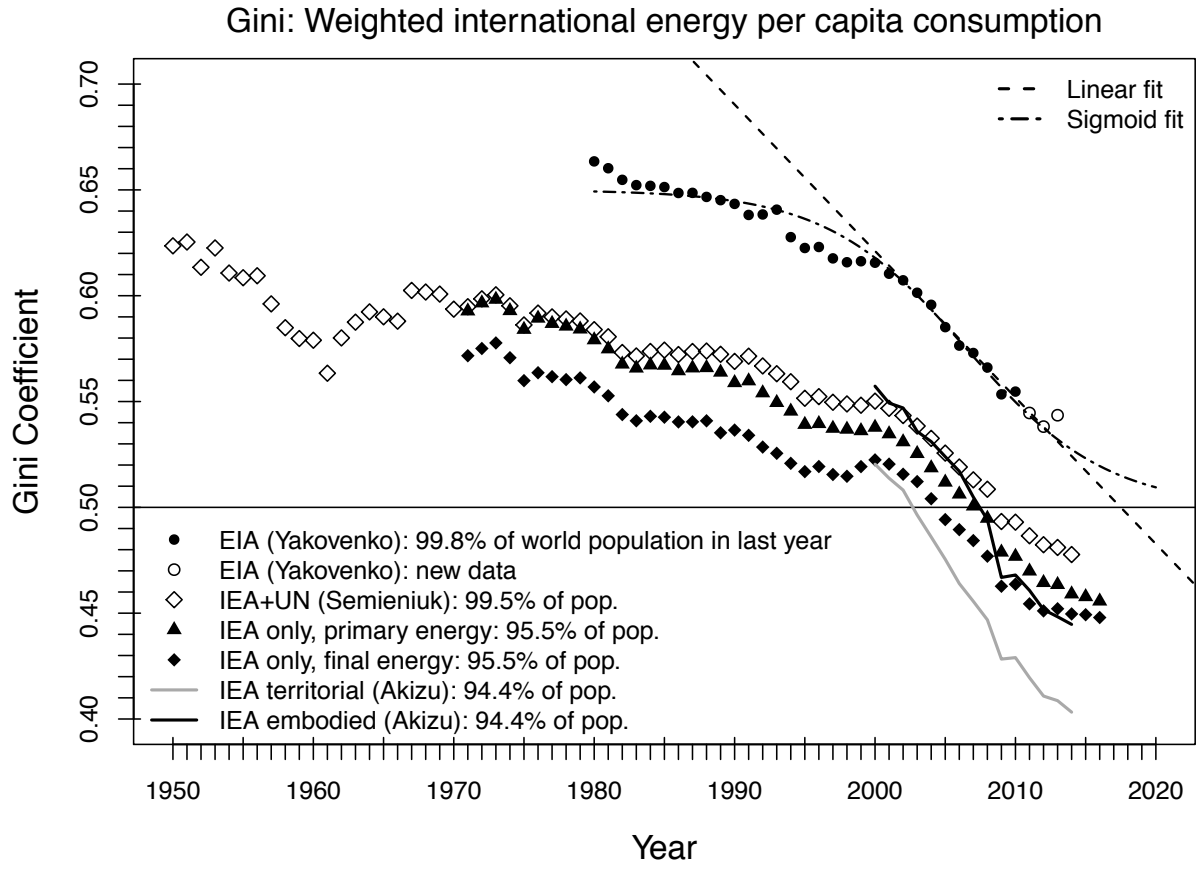
2. Energy Inequality Re-estimated

A statistical mechanic perspective on economic inequality suggests to explain the equilibrium distribution as the result of a process whereby the economic resource is exchanged between agents under certain constraints (Banerjee and Yakovenko, 2010). An analogy with the microcanonical ensemble in statistical mechanics is made by assuming that the total amount of the resource and the number of agents over which the resource is partitioned are held constant and that the process is ergodic. By far the most likely and hence maximum entropy or 'statistical equilibrium' distribution is the Boltzmann-Gibbs distribution. Under the given assumptions it is exponentially distributed. Evidence that this predicts many national income distributions apart from the richest few percent is in Tao et al. (2019). What makes the exponential prediction particularly powerful from an inequality perspective is that it implies a Gini coefficient of 0.5, regardless of the distribution's

parameter, the mean (Dragulescu and Yakovenko, 2001), which is unique among the canonical probability distributions.[2]

Extending the maximum entropy reasoning to a global income distribution is difficult, however, as there is no single correct exchange rate, and purchasing power parity estimates vary between methods and over time (Anand and Segal, 2015; Shaikh and Weber, 2018). Yakovenko and co-authors therefore propose that focussing instead on energy consumption circumvents this accounting problem: a Joule is a Joule regardless of context (Lawrence et al. 2014). This paper, however, shows that the statistical equilibrium results for energy consumption depend on the choice of method of accounting for energy consumption: what counts as a Joule depends on how we decide to count.

Figure 1: Time series of weighted international inequality in energy consumption measured by the Gini coefficient for various ways of accounting for energy consumption. See appendix A for data sources.



Empirical analysis in Lawrence et al. (2014) of the Energy Information Agency (EIA) dataset shows that weighted international inequality in energy consumption is indeed converging to a 0.5 Gini along an S-curve trajectory from above. This pattern is confirmed by more recent

[2] This is because the Gini coefficient is scale invariant, i.e. if all incomes are scaled by the same factor (and so is the mean), the Gini coefficient stays constant. Since the exponential distribution's only parameter is the mean, the Gini is the same for this family of distributions. Note that this holds for all scale invariant inequality measures: for instance, the Atkinson measure of the exponential distribution is $I = 1 - (\Gamma(\eta + 1))^{\frac{1}{\eta}}$, only dependent on the inequality aversion parameter η of Atkinson measure, but not on the distribution's parameter. See the Appendix B for a derivation.

vintages of the EIA data that appeared after the publication of their results (see Figure 1). However, our analysis of five other datasets that use different methods of accounting for energy consumption shows that the Gini does not converge to 0.5. Instead, all five datasets start with Gini coefficients above 0.5 but fall to values significantly below 0.5 between 2003 and 2009 (also Figure 1, see appendix A for data source description). Therefore, the maximum entropy-based prediction of an exponential distribution cannot be confirmed across methods of accounting for energy consumption.

3. Accounting for Energy Consumption

The key to our finding that the statistical equilibrium prediction does not hold across datasets is that multiple reasonable methods exist for summing heterogeneous energy carriers such as coal, oil, hydro or wind. Just like for currencies, in the messy reality of economics, there is no one right way of accounting for energy. Unlike in physics, in social accounting for energy a Joule is not a Joule independent of the method of its generation, the form of its use or the point of measurement in the sequence of conversion.

Energy values are calculated according to the heat content of an energy carrier, however, there are at least three different ways of accounting for primary energy. The first method asks what is the equivalent amount of fossil fuels needed to produce some amount of energy from non-combustible sources and is called the substitution method. This is the accounting method used by the Energy Information Agency (EIA) data underlying Yakovenko's results. For instance, electricity from hydro is accounted for with the heat content of fossil fuels required to produce the same amount of electricity. With a conversion efficiency from chemical energy in coal to electricity of 37%, this implies hydro electricity is multiplied by almost three and then added to energy from fossil fuels. Second, the physical content method asks what is the first form in which the energy from an energy carrier can be used for multiple purposes. For example, for hydro the first form of energy that can be used for multiple purposes is electricity. For nuclear energy on the other hand, the thermal energy from fission is that first form: it could be converted into electricity but also used directly as heat. This method is employed by the International Energy Agency (IEA) whose data underpin all time series in Figure 1, other than that of Yakovenko's EIA-based series. The third method called direct equivalent and used in the International Panel on Climate Change (IPCC) uses the heat content of electricity for all non-combustible energy carriers.

Note, fossil fuels are accounted in the same way in all three methods as the reference energy carrier. So the key difference between the three methods is the treatment of non-fossil fuels. Table 1 illustrates the different energy balances for a hypothetical situation with only fossil, hydro and nuclear power.[3] For example, hydro power is accounted as 2.7 J/s when using the substitution method but only as 1 J/s with the physical content method. Though less stark, the two methods also yield different results for nuclear due to varying assumptions about conversion efficiencies. See Koomey et al. (2019) and Macknick (2011) for further discussion.

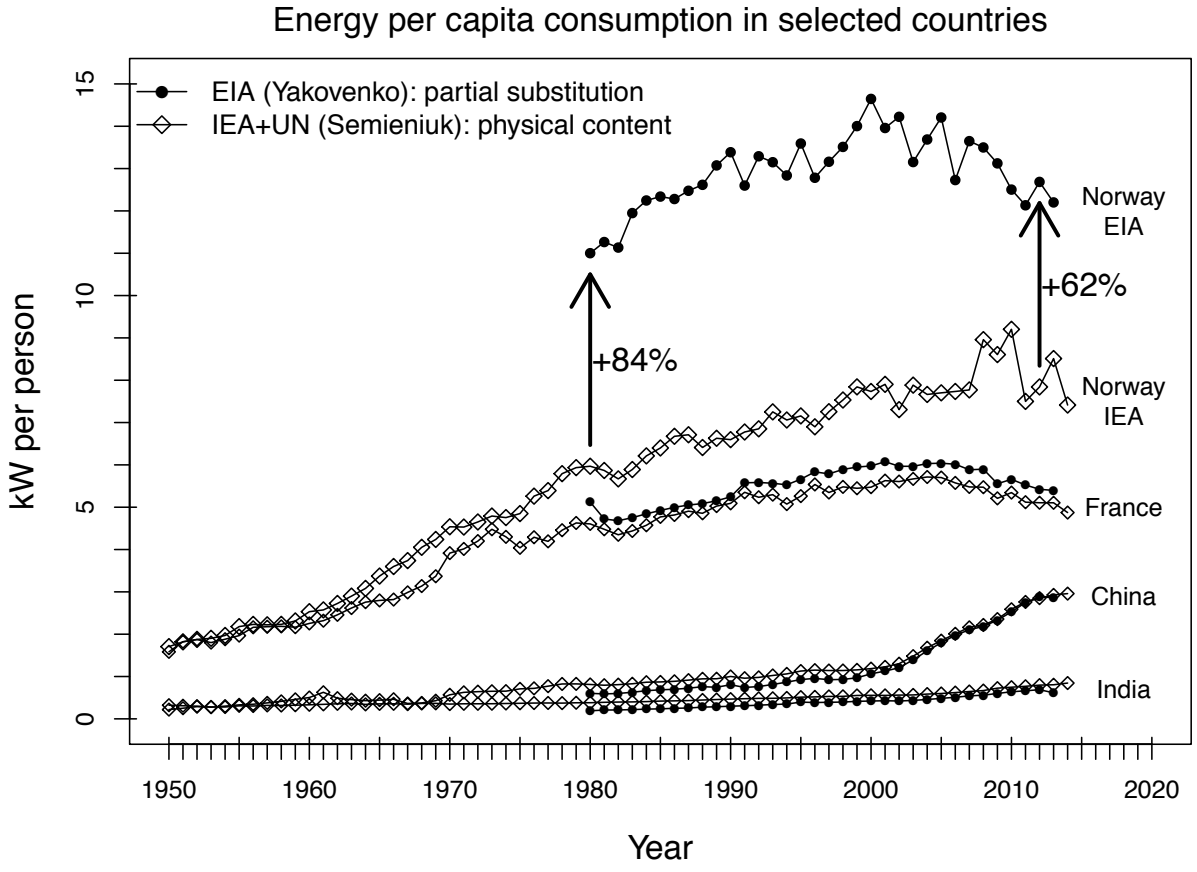
Table 1: Hypothetical primary energy balance for three accounting methods

	Substitution (e.g. EIA) in J/s	Physical Content (e.g. IEA) in J/s	Direct Equivalent (e.g. IPCC) in J/s
Fossil fuels	1.00	1.00	1.00
Hydro	2.70	1.00	1.00
Nuclear	3.07	3.03	1.00
Total	6.77	5.03	3

[3] The partial substitution primary energy to electricity conversion efficiencies of hydro (37.0%) and nuclear (32.6%) are calculated from Table A6 in (EIA, 2019) and the physical content 33% efficiency for nuclear from (Krey et al., 2014).

When accounting for the primary energy demand of a country, the choice of method can make a dramatic difference. This is illustrated in Figure 2 for Norway, a country that generates 99% of its electricity from hydro. Using the substitution method of the EIA, Norway is found to consume more than 1.6 times as much energy per capita as compared to the physical content method employed by the IEA. But even for countries with a large nuclear share in their energy mix such as France the difference is significant. Given that rich countries tend to have a more diverse energy mix compared to a high degree of fossil fuel and combustible bio mass dependence of poor countries, the EIA data also ascribes higher values to energy rich countries and lower values to energy poor countries (see China and India in Figure 2). This explains the higher inequality for EIA data in Figure 1. Hence, the confirmation of the statistical equilibrium prediction of an exponential distribution hinges on the method of accounting and is therefore not a robust one. Importantly, the only method for which this prediction holds is precisely the one that is least suitable for accounting for renewable energy and hence informing climate policy's attempts at improving energy efficiency, as it masks an improvement in conversion efficiency of primary to secondary energy (Koomey et al. 2019). As nuclear energy is consumed mainly in energy rich countries, the direct equivalent method of primary energy accounting is likely to produce even lower inequality estimates.

Figure 2: Primary energy demand in a selection of countries as measured by the partial substitution method in the EIA (black) and physical content method in the IEA (red).



But the problems with energy accounting do not stop with how we define primary energy. A further ambiguity stems from attributing primary energy either to the territory where it enters production (territorial measurement, used in all datasets discussed so far); or to the country where the final goods produced with the help of energy are consumed, the energy footprint

measurement (Peters et al., 2017). Which of these two measures is more suitable depends on the economic question one wishes to address. For our analysis, what matters is that both measurements refute the statistical equilibrium prediction: Akizu-Gardoki et al. (2018) have recently estimated the energy footprint for most of the world. Even though its inequality is higher than a territorial estimate for the same population, the footprint Gini also falls significantly below the 0.5 predicted value instead of converging to it (see black and grey lines in Figure 1).

Finally, energy can also be measured at different stages in the conversion chain (somewhat analogous to pre or post tax income). Primary energy, which has been discussed so far considers both the energy needed by the energy sector to convert energy to the state in which it is used by end users, e.g. the energy needed to refine oil and transmit and distribute electricity, and the energy consumed by end users. Final energy on the other hand counts only the energy reaching end users. Figure 1 also shows inequality in final energy consumption which is even lower as it disproportionately reduces energy consumption in very high primary energy per capita countries such as OPEC oil producers.

The overarching insight is that the maximum-entropy derived prediction of an exponential distribution is not robust. Different data sources, and different accounting conventions produce various results, and all but one measure do not converge to the unique Gini predicted with maximum-entropy reasoning.[4]

4. Discussion

The results about the distribution of energy consumption that emerge by viewing the problem through a maximum entropy lens provide a starting point for an urgently needed better understanding of the patterns of global energy inequality. This paper has shown, however, that the bold hypotheses from statistical mechanics about the equilibrium energy inequality are not robust when confronted with different methods of constructing the data. Only for primary energy that is accounted for according to the substitution method do the results hold, but this is precisely the method least suited for climate policy analysis as it poorly represents renewable energy sources. The sensitivity to accounting methods is particularly problematic for a maximum entropy approach, since it claims that its predictions only rely on combinatorial reasoning under given constraints. The selection of an accounting method and introduction of a new constraint to represent it cannot be resolved in any objective way by more information as the principle of maximum entropy would postulate (Yang, 2018). Unlike in physics, accounting for social phenomena relies heavily on conventions without any clear ‘right’ or ‘wrong’ method, which has been illustrated here for the case even of a seemingly homogenous, physical quantity. This reflects the differences in the basic nature and structure of social and physical reality that requires different ontologies in the social and natural sciences including economics (see e.g. Lawson, 2019 pp. 2-28). Without a study of the nature of the things being measured, empirical knowledge about the things that matter and an economic or other social theory that connects them to the problem at hand (e.g. climate change), maximum entropy reasoning cannot decide what accounting method is more suited to the problem of energy consumption inequality or, for that matter, any social accounting problem.

Lawrence et al. (2014) attempt to circumvent the ambiguity of an income measure by finding another measure. We have demonstrated in this paper that this other ostensibly determinate

[4] Additional complications would arise from taking into account inequality in access to certain energy carriers (e.g. electricity) and services (clean cooking stoves), i.e. energy quality (Dubois and Meier, 2016; Fouquet, 2016; Rao and Pachauri, 2017). And while final energy is currently the best approximation to energy services, for which data is available for most countries, useful exergy would be a more accurate measure of the energy inequality that ultimately matters (Heun and Brockway, 2019; Sousa et al., 2017).

measure is not unambiguous either. Given the fundamental reliance on social accounting, which is conventional, rather than exact, we are sceptical that any one measure can be found that would be unambiguous. In sum, a maximum entropy approach to economic problems only has a chance at predicting, when it is embedded in the appropriate social context which needs to be detected with knowledge of the concrete empirical problem understood via a social theory. Therefore, maximum entropy reasoning can be a tool to operationalize economic theory but cannot substitute for either theory or context-driven empirical analysis.[5]

Apart from these epistemological aspects, the great variation of Ginis across different accounting methods also highlights more general, practical difficulties for policy making towards climate change mitigation. The variance in Ginis implies that at present there is no way of objectively determining the distribution of energy consumption levels across countries. If mitigation policies are meant to be in relation to current consumption levels, this means that we are lacking a reliable point of reference. Beyond the lack of knowledge about the present state of global energy inequality, the failure of the maximum entropy programme to robustly predict the Gini value to which the world is converging also means that we lack predictive tools needed for policy projections.

As a silver lining, another regularity robustly manifests across all measures of energy consumption: the s-curve shape of Gini values from about the 1990s onwards which Yakovenko and co-authors found based on their maximum entropy reasoning. All measures display an s-curve, only at different levels. Crucially, while the maximum entropy perspective is frequently employed searching for equilibria, the actual data seems to suggest that there are repeated s-curves or transitions (see the series based on Semieniuk 2018 for an additional one in the 1950s). To further theorise this finding, it could be linked to developmental patterns and processes of evolutionary change rather than convergence to some unique and stable equilibrium. The new ways of looking at data that maximum entropy reasoning encourages are instrumental in discovering such patterns. But to gain an understanding of the underlying drivers we need to also draw on insights from economic history and theory.

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Appendix A: Data Sources

This paper uses energy balances data from the International Energy Agency (IEA), the Energy Information Agency (EIA) and the United Nations (UN), which are detailed below. Population data is taken from the 'indicators' supplied both by the IEA and EIA databases, and from Penn World Table and Maddison Project Statistics for periods non available in the IEA dataset (for details see Semieniuk 2018).

[5] For attempts to join maximum entropy reasoning about observed distributions with economic theory see Scharfenaker & Semieniuk (2017) and dos Santos & Scharfenaker (2019), and to provide a general principle dos Santos (2017). Farjoun and Machover (1983) and Foley (1994) discuss conceptual foundations.

EIA: Primary Energy
Primary energy data from the EIA is available freely from its website (EIA 2019), and has the widest coverage of countries (nearly 100% of the world's population covered). Surprisingly the geographical coverage has actually decreased since the paper by Lawrence et al. (2014) has been published, for instance data for Bermuda in the current, 2019 web download interface, is only available from 1988, while the version on which Lawrence et al. (2014) run their calculation includes Bermuda's data from 1980. The data has not been updated beyond 2013. The three newest data points are from the 2019 data, the others from Lawrence et al. (2014) who have made available their data as open source supplementary material.

IEA: Primary and Final Energy
The IEA covers a comprehensive set of countries' energy balances both for primary and final energy starting in 1971. In the last year of data, 2016, about 95.5% of global population are covered. Data are available against a fee from International Energy Agency (2018).

IEA and UN: Primary Energy
To extend the data series in the IEA to more countries and backwards in time beyond the year 1971, Semieniuk (2018) has spliced the data with the United Nations Energy Statistics (2016) database which contains primary energy data starting in 1950, and from additional sources for non-commercial use of biomass. The resulting dataset covers upward of 98% of population for every year after 1970 and above 92% before that. Note that the one-time low energy inequality in 1961 is due to China's rapid increase that year in energy consumption under the 'Great Leap Forward' programme (Semieniuk 2018).

Territorial and Consumption-Based Primary Energy
Akizu-Gardoki et al. (2018) have used the 26 sector multi-sectoral input-output database from Eora and IEA sectoral energy demand to reconstruct the flows of embodied energy in trade, and arrive at the footprint of energy consumption, i.e. the sum of a country's consumption of energy directly on its territory and the net imports of energy embodied in manufactured commodities and international services. Due to merging different databases they arrived at an intersection of 126 countries, which cover 94.4% of population on average.

Appendix B: Derivation of the Atkinson Inequality for the Exponential Distribution

The Atkinson index of inequality, I, is defined as

$$I = 1 - \frac{y_{ede}}{\mu} \qquad (1)$$

where μ is the mean holding per person of the resource over which inequality is measured, e.g. income or energy, and y_{ede} is the equally distributed equivalent income that would suffice to make society as well off as the actual, unequally distributed income according to a social welfare function (Atkinson, 1970). It is defined as

$$y_{ede} = \left(\int_0^\infty f(y) y^\eta \, dy \right)^{\frac{1}{\eta}} \qquad (2)$$

where y is income, η is the inequality aversion parameter of the social welfare function and f(y) the density. If f(y) is exponential then

$$y_{ede} = \left(\int_0^\infty \lambda e^{-\lambda y} y^\eta \, dy \right)^{\frac{1}{\eta}} \qquad (3)$$

where the integral is the Gamma function $\Gamma(x)$, therefore

$$y_{ede} = (\lambda^{-1}\Gamma(\eta+1))^{\frac{1}{\eta}} \qquad (4)$$

Plugging this back into the inequality measure in (1) and noting that the exponential distribution parameter is the inverse of the distribution's mean $\lambda = 1/\mu$, we have

$$I = 1 - \left(\Gamma(\eta+1)\right)^{\frac{1}{\eta}} \qquad (5)$$

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